Method for Detecting the Appropriateness of Wearing a Helmet Chin Strap at Construction Sites

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***Abstract*—A novel method for verifying the proper use of helmet chin straps during clothing inspections at construction sites is proposed, prioritizing safety in construction environments. As the problem statement, existing helmet-wearing state detection systems often rely on approaches that might not be optimal. This research aims to address limitations in single-view detection and proposes a multi-view deep learning approach for improved accuracy. The proposed method leverages transfer learning for object detection using well-known models such as YOLOv8 and Detectron2. The annotation process for detecting helmet chin straps was conducted using the COCO format with the assistance of Roboflow. Through experimental analysis, the following findings were observed: Using images captured simultaneously from two different angles of the chin strap condition, Detectron2 demonstrated a remarkable ability to accurately determine the state of helmet usage. It could identify conditions such as the chin strap being removed or loosely fastened with 100% accuracy.**

***Keywords*—Detectron2; safety-first construction; helmet chin strap; annotation; roboflow; COCO annotator; YOLOv8**

I. Introduction

At construction sites, workers are typically subjected to a clothing check before starting their tasks to ensure that all safety equipment, including work clothes and helmets, is worn correctly. A critical component of this safety check is the proper fastening of helmet chin straps. If a chin strap is not properly tightened, the helmet may dislodge during a fall, crash, or other impact, potentially leading to serious head injuries or fatalities.

According to the 2022 Occupational Accident Occurrence Status published by the Ministry of Health, Labor, and Welfare, the construction industry reported a total of 14,539 casualties from occupational accidents. Among these, falls were the most common, accounting for 4,594 cases (31.6%), followed by falls from heights (1,734 cases, 11.9%) [1]. This underscores the critical importance of wearing helmets correctly and checking their fit.

Currently, clothing checks, including helmet inspections, are performed visually by humans. This method can introduce variability in judgment criteria depending on the individual conducting the inspection, and it incurs significant personnel costs. Therefore, there is a need for a more efficient and consistent approach to these safety checks.

Research objective is to develop an AI-based clothing inspection system for construction workers that reduces personnel costs and ensures consistent inspection standards. A key feature of this system is the automatic detection of helmet chin straps, a task that is unprecedented and considered highly challenging. By automatically detecting the chin strap, the system can assess whether the helmet is worn correctly and if the chin strap is securely fastened.

Methodology used to achieve this objective, the following methodology and procedures are adopted:

Image Annotation and Augmentation: Annotate images to represent various states of chin strap usage. Augment these images to enhance the machine learning dataset.

Transfer Learning: Apply transfer learning techniques to the image data, specifically focusing on helmet chin straps, using advanced object detection models like YOLOv8 [1] and Detectron2[2].

AI Object Detection Application: Utilize AI object detection to identify chin straps in images of construction workers wearing helmets.

Experiment and results show that annotations were performed using the COCO format[3] via Roboflow[4], and transfer learning was applied to the annotated data. Experimental results indicated that Detectron2 could determine the helmet's wearing state (e.g., chin strap removed or loose) with 100% accuracy based on images taken from two different angles simultaneously.

In conclusion, the developed AI-based system for checking the appropriateness of wearing helmet chin straps at construction sites demonstrates high accuracy and consistency, addressing the limitations of human visual inspections. This system not only enhances safety by ensuring proper helmet usage but also reduces the need for manual inspections, thereby cutting down on personnel costs.

Related research works are described in the next section followed by the proposed method. Then, experiment method and result are described followed by conclusion with some discussions.

[1] https://github.com/ultralytics/ultralytics
[2] https://github.com/facebookresearch/detectron2
[3] https://cocodataset.org/#home
[4] https://roboflow.com/universe

II. Related Research Works

Examples of helmet-wearing state detection systems using object detection AI include:

"Detection of people not wearing helmets" by SOREST Corporation [2]

"AIJO® Safety Series" by COMSYS Information Systems Co., Ltd. [3], [4]

"Helmet Detection" by AID Co., Ltd. [5]

These systems commonly detect the presence or absence of a helmet but cannot assess the state of the chin strap. Another system, Hertz Electronics Co., Ltd.'s helmet wearing sensor "ENS-HH01" [6], uses a built-in sensor to detect if the chin strap is loose or the buckle has come off. However, it requires the sensor to be physically attached to the chin strap.

Based on the review above, there is no precedent for a system that detects whether a helmet is being worn correctly by analyzing the chin strap using object detection AI. This research introduces such a system, addressing this significant gap in current safety inspection technologies.

As for related research works to the object detection, there are the followings: Embedded object detection with radar echo data by means of wavelet analysis of MRA: Multi Resolution Analysis is proposed [7]. Method for support length determination of base function of wavelet for edge and line detection as well as moving object and change detections is also proposed [8]. On the other hand, visualization of 3D object shape complexity with wavelet descriptor and its application to image retrievals is introduced [9]. Meantime, method for 3D object recognition using several portions of 2D images through different aspects acquired with image scope included in the fiber retractor is proposed [10]. Meanwhile, method for 3D rendering based on intersection image display which allows representation of internal structure of 3D objects is proposed [11].

Method for object motion characteristics estimation based on wavelet Multi resolution Analysis: MRA is proposed [12]. On the other hand, modified seam curving changing resizing depending on the object size in time and space domains is conducted [13]. Meanwhile, object detection system to help navigating visual impairments is created [14]. Meantime, detection objects using Haar cascade[5] for counting number of humans implemented in OpenMV[6] is proposed [15].

Image retrieval method based on hue information and wavelet description-based shape information as well as texture information of the objects extracted with dyadic wavelet transformation is proposed [16]. Also, method for 3D object of content representation and manipulations on 2D display using human eyes only is proposed [17]. On the other hand, object classification using a deep convolutional neural network and its application to myoelectric hand control is proposed [18] together with object classification with deep convolutional neural network using spatial information [19].

Development of a prosthetic hand control system Based on general object recognition analysis of recognition accuracy during approach phase is conducted [20]. Meanwhile, extraction of dynamic moving feature of rotating objects with wavelets is proposed and demonstrated [21].

Intelligent method for 3D image display with semitransparent object representations is proposed in study [22]. On the other hand, real time wheeled soccer robot omnidirectional image object tracking using faster region based convolutional neural network is proposed and created [23].

III. Proposed Method

Process flow of the proposed method and system is shown in Fig. 1. When workers' face image acquisition from the front and the side view, authentication is performed followed by cloth check. Safety shoes, harnesses, helmet (including chin strap appropriateness) are checked. In these processes, object detection model (YOLOv8 or Detectron2) is required together with annotation (COCO Annotator) of these items. Once the trained object detection model is created, then the cloth check can be done using the front and the side view images of workers.

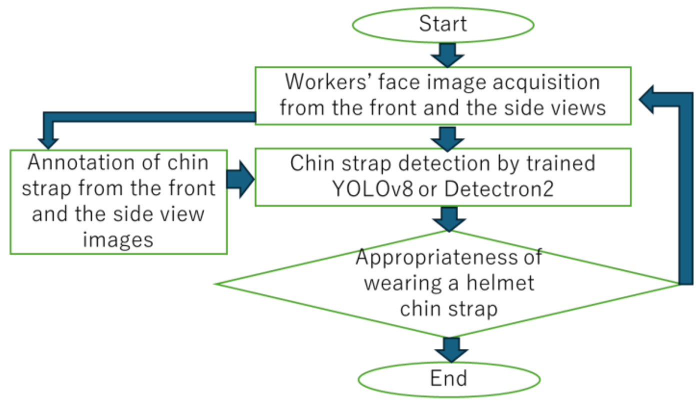


Fig. 1. Process flow of the proposed method for checking the appropriateness of wearing a helmet chin strap.

The required processes of the proposed method are as follows,

1) Annotation with acquired images

2) Training data collection with augmentation

3) Training of the object detection models of YOLOv8 and Detectron2 as well as deployment of the models

The detailed descriptions for these are as follows:

A. Data Collection and Augmentation

Since AI object detection relies on learning from image data, we acquired images of workers wearing helmets. To increase the amount of training data and improve model robustness, we employed data augmentation techniques. This process involves manipulating existing images through methods like rotation, scaling, and color jittering, essentially creating variations of the original data. This allows the model to learn the target object (chin strap) under various conditions, enhancing its generalization capabilities.

[5] https://github.com/opencv/opencv/tree/master/data/haarcascades

[6] https://openmv.io/

B. *Image Annotation for Accurate Detection*

Following augmentation, we meticulously annotated the chin straps in the images using a tool named COCO Annotator [24][7], as shown in Fig. 2.

Fig. 2. Example of the annotated image using coco annotator.

This tool facilitates the creation and management of image annotations in the COCO format, a popular standard for object detection datasets. We employed polygon segmentation, a technique that precisely outlines the chin strap's shape in each image. This detailed annotation empowers the AI model to distinguish the chin strap from other elements in the image with greater accuracy.

C. *Model Development and Deployment*

Leveraging the annotated image dataset, we built a deep learning model using Detectron2 [25], a well-established object detection library. Through the training process, the model learns to identify the specific features of a helmet chin strap within an image. Once trained, the model can be integrated with a camera system, enabling real-time detection of chin straps in live video feeds.

IV. Experimental Method and Results

A. *Data Augmentation for Enhanced Model Generalizability*

To enrich the training dataset and improve the model's ability to handle real-world variations, we employed data augmentation techniques on the images captured from three viewpoints (front, right side, left side). As illustrated in Fig. 3, these techniques included the followings:

1) *Random rotation*: Images were randomly rotated within a range of -10° to 10°, simulating scenarios where workers might be positioned at slight angles relative to the camera.

2) *Sandstorm-like noise injection*: We introduced artificial noise to the images, mimicking real-world conditions with reduced visibility due to dust, rain, or other environmental factors. This helps the model learn to detect chin straps even under less-than-ideal conditions.

Combined Augmentation: We also applied a combination of rotation and noise injection to create even more diverse training data.

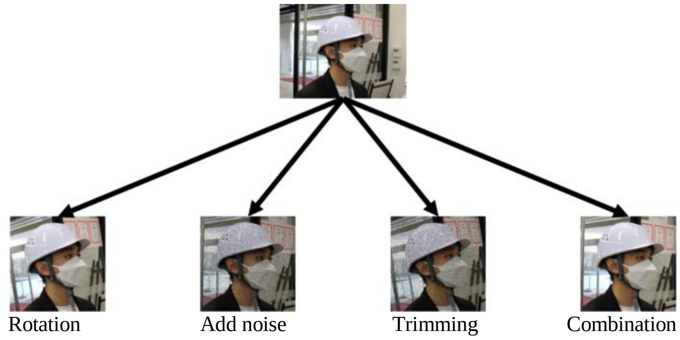


Fig. 3. Augmentation.

Furthermore, all images, including those generated through augmentation, were resized to a standard dimension of 800 by 800 pixels for consistency within the dataset. This standardization simplifies processing for the deep learning model.

By incorporating these variations, we effectively quadrupled the amount of training data available, enhancing the model's robustness and generalizability to real-world scenarios.

B. *Refining the Training Dataset for Improved Detection*

Following data augmentation, we meticulously annotated the chin straps in the images using COCO Annotator. A new label, "helmet-chinstrap", was created and applied to each chin strap instance. We then initiated training using Detectron2 on this initial set of 60 images.

However, to achieve robust detection of chin straps from various angles, particularly diagonal and sideways views, we acknowledged the limitations of the initial dataset. To address this, we expanded the training data by collecting additional photographs:

Workers wearing helmets from diagonal and sideways angles broadened the model's exposure to real-world scenarios beyond frontal views.

Workers with improper helmet use: Images depicting loose chin straps or no chin straps were included to enhance the model's ability to identify deviations from proper helmet wear.

These additional images were captured not only from the sides but also from both left and right diagonal viewpoints. It's important to note that frontal views were intentionally excluded to focus on the previously underrepresented angles.

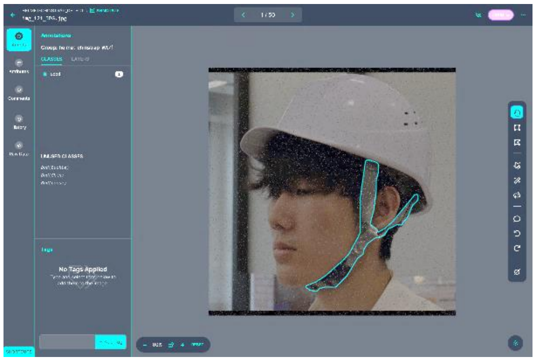
The newly collected images underwent the same augmentation and annotation processes described earlier. This diligent approach significantly increased the training data size from 60 to 283 images.

C. *Enhancing Efficiency with Roboflow*

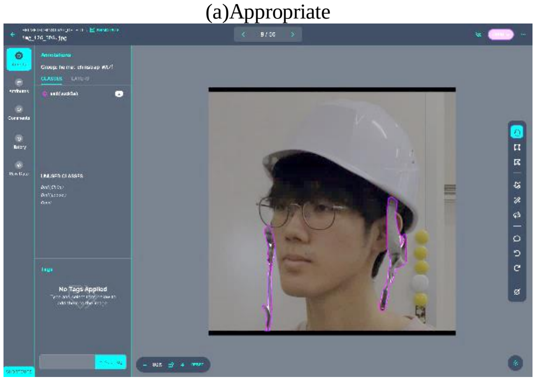
Recognizing the potential for improved efficiency, we adopted Roboflow [26] as our primary platform for data augmentation and annotation. Roboflow is a comprehensive AI development tool that streamlines the entire process, from creating training data through augmentation and annotation to building the final learning models. Notably, Roboflow's

[7] https://github.com/jsbroks/coco-annotator

annotation functionality offers a valuable feature: when an object is selected within an image, it automatically performs polygon segmentation, significantly reducing annotation time (see Fig. 4).



(a)Appropriate



(b)Not appropriate

Fig. 4. Examples of annotated images by Roboflow.

By leveraging Roboflow's capabilities, we were able to streamline the data preparation process and expedite the creation of a more robust training dataset.

D. *Leveraging YOLOv8 for Enhanced Detection Accuracy*

In our pursuit of optimal chin strap detection accuracy, we strategically transitioned from Detectron2 to YOLOv8 [27] as the object detection library for transfer learning within our deep learning model. YOLOv8 is recognized for its superior accuracy compared to Detectron2, making it a more suitable choice for this critical task.

E. *Expanding Label Granularity for Comprehensive Detection*

Furthermore, to effectively detect chin straps even in scenarios of improper helmet use, we refined our annotation approach. During the annotation process, we created and implemented additional labels for various helmet wearing conditions. These labels went beyond simply identifying the chin strap and encompassed situations such as loose chin straps or missing chin straps altogether. By incorporating this expanded labeling scheme within our training data, we empowered the model to not only detect the presence of a chin strap but also to classify the specific way the helmet is being worn.

F. *Transfer Learning with YOLOv8*

With the enhanced training data incorporating the new helmet condition labels, we performed transfer learning using YOLOv8. This process leveraged the pre-trained knowledge of YOLOv8 on general object detection and adapted it to the specific task of identifying and classifying chin strap states within our helmet usage context. This resulted in the creation of a highly optimized deep learning model specifically tailored for our chin strap detection requirements.

G. *Rigorous Training and Evaluation*

For optimal model training, the dataset was strategically divided into the followings,

1) *Training data (245 images)*: This primary set provided the foundation for YOLOv8's learning process.

2) *Validation data (42 images)*: This subset served as a critical checkpoint to monitor the model's performance during training and prevent overfitting.

3) *Test data (63 images)*: This unseen data provided a final assessment of the model's generalizability and ability to perform effectively on new examples.

We then leveraged YOLOv8 for transfer learning on the training data. The achieved results were demonstrably superior to those obtained with Detectron2, as illustrated in Fig. 5.

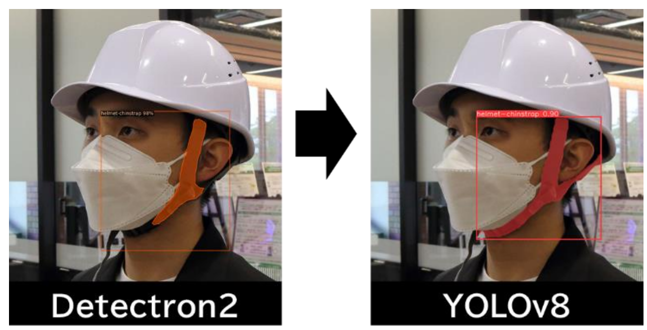


Fig. 5. Comparison of helmet chin strap detection performances between Detectron2 and YOLOv8.

YOLOv8 exhibited the following several key advantages:

1) *Expanded detection area*: The model accurately identified the chin strap across a larger image region, encompassing even partially obscured areas.

2) *Enhanced front-facing detection*: YOLOv8 excelled at detecting chin straps in frontal views, where they might follow the facial contours or be hidden behind the chin, posing a challenge for traditional methods.

Overall, a significant improvement in detection accuracy was confirmed compared to Detectron2. This translated into the model's ability to reliably detect a wider range of chin strap conditions, including the followings:

1) *Loose chin straps*: The model can effectively identify situations where the chin strap is not properly tightened.

2) *Missing chin straps*: Scenarios where the helmet is worn without the chin strap fastened are accurately detected.

3) Other variations: YOLOv8 demonstrates robustness in detecting chin straps in various lighting conditions, backgrounds, and partial occlusions.

H. Enhanced Chin Strap Detection for Various Wearing Conditions

Building upon the success of YOLOv8 for chin strap detection, we further refined our approach to encompass diverse helmet wearing states. This section details the creation of a labeling scheme and the evaluation of detection accuracy for the following three specific conditions:

1) Properly worn: This scenario represents the ideal state where the helmet is securely fastened with the chin strap tightened.

2) Unbuckled buckle: This condition signifies that the chin strap buckle is not engaged, potentially compromising helmet security.

3) Loose chin strap: This scenario identifies situations where the chin strap is not properly tightened, potentially allowing the helmet to come loose during an impact.

I. Helmet Wearing State Annotation

To effectively detect these various wearing states, we expanded the annotation process within Roboflow. New labels were created and assigned to each image based on the observed helmet condition. This enriched labeling scheme provided the model with the necessary information to distinguish between different wearing scenarios.

J. Data Augmentation and Training

The data augmentation techniques remained largely consistent with the previous approach. Images were subjected to random rotations within a -10° to 10° range, and sandstorm-like noise was introduced to simulate challenging real-world conditions. This process enhanced the model's generalization capabilities and robustness to variations in lighting, background, and partial occlusions.

K. Evaluation of Detection Accuracy

The learning results for the three wearing conditions are presented in Fig. 6 as follows,

1) Properly worn: We achieved remarkable detection accuracy for properly worn helmets, with successful detection from both frontal and side views. This confirms the model's ability to effectively identify helmets secured in the optimal configuration.

2) Unbuckled buckle: Detection accuracy for unbuckled buckles proved to be excellent from the front view, as shown in Fig. 6. However, detection from the side exhibited an accuracy of 80%, suggesting a potential area for further improvement.

3) Loose chin strap: The system demonstrated a detection accuracy of 60% for loose chin straps from the front view (see Fig. 6). This indicates some room for enhancement. In contrast, detection accuracy from the side view reached a commendable 90%, highlighting the model's proficiency in identifying this condition under side-angle perspectives.

(a) Front view (b) Side view

Fig. 6. Loose helmet chin strap.

L. Detailed Analysis of Loose Chin Strap Detection

Within the "loose chin strap" category, we identified the following two distinct scenarios:

1) Chin strap above chin: This situation occurs when the chin strap is fastened but rests above the wearer's chin, potentially compromising its effectiveness.

2) Chin strap loose under chin: This scenario represents a loose chin strap positioned beneath the chin, offering some level of protection but not secured optimally.

Interestingly, the model exhibited a clear preference for detecting these variations based on the following viewpoints:

1) Front view: Detection accuracy for loose chin straps was more effective when the chin strap was positioned above the chin.

2) Side view: Conversely, detection from the side proved considerably more accurate when the chin strap was loose under the chin.

This observation suggests a potential strategy for future optimization. Namely, the model might be trained to leverage a combination of frontal and side-view detection to achieve comprehensive and robust identification of loose chin straps regardless of their specific position relative to the chin.

Table I provides a comprehensive overview of the detection accuracies achieved for all five helmet-wearing conditions.

TABLE I. DETECTING ACCURACY

Image_Used	Properly	Unbuckled	Loose	Loose(up)	Loose(down)
Front_view	100.0	100.0	57.1	100.0	40.0
Side_view	100.0	83.3	85.7	50.0	100.0
Both	100.0	100.0	100.0	100.0	100.0

M. Challenges of Single-View Detection and Proposed Multi-View Solution

Our analysis revealed limitations associated with relying solely on a single viewpoint for detecting loose chin straps and unbuckled buckles as follows,

1) Unbuckled buckles: While frontal views excelled at detecting unbuckled buckles, side views might miss instances where the remaining strap points in the direction of detection.

This highlights the potential for misclassification if only a single viewpoint is considered.

2) Loose chin strap variations: The model demonstrated a dependency on viewpoint for detecting loose chin strap variations. Frontal views were more effective for chin straps positioned above the chin, while side views excelled at detecting loose straps under the chin. This suggests a single viewpoint might not capture the full spectrum of loose chin strap configurations.

To address these limitations, we propose a multi-view detection approach. By simultaneously analyzing images from both frontal and side viewpoints, the model can achieve more comprehensive and robust detection of various helmet wearing states. The followings are how it would work:

1) Combined detection: The system would process images from both the front and side, leveraging the strengths of each viewpoint.

2) Independent judgment: Each viewpoint would independently assess the helmet wearing state (properly worn, unbuckled, loose).

3) Final classification: If either viewpoint identifies inappropriate wear (unbuckled, loose), the overall classification would be "inappropriate wear." This ensures a stricter safety standard, catching potential safety hazards even if missed from one viewpoint.

This multi-view approach offers the following several advantages:

1) Improved accuracy: By combining information from multiple perspectives, the system can achieve a higher overall detection accuracy for various helmet wearing conditions.

2) Enhanced robustness: The system becomes less susceptible to limitations inherent in any single viewpoint, resulting in a more robust and reliable detection solution.

3) Increased safety: The stricter safety classification based on "either viewpoint detecting inappropriate wear" minimizes the risk of missed detections and promotes a safer work environment.

N. Novelty and Contribution

This multi-view detection approach represents a significant contribution to the field of helmet wearing state detection systems. By leveraging object detection AI to analyze chin straps from multiple viewpoints, our system offers a unique and effective solution that surpasses existing technologies.

V. CONCLUSION

Ensuring proper helmet usage is paramount in construction sites to protect workers from head injuries. This paper proposes a novel method for detecting the appropriateness of helmet chin strap wear during safety checks.

As the problem statement, existing helmet wearing state detection systems often rely on approaches that might not be optimal. This research aims to address limitations in single-view detection and proposes a multi-view deep learning approach for improved accuracy.

In the proposed method, we leverage transfer learning with well-established object detection libraries like YOLOv8 or Detectron2. Roboflow is employed for efficient image annotation using the COCO format to train the model on helmet chin straps.

The key innovation lies in the multi-view approach of which images are captured simultaneously from both the front and side of the worker wearing the helmet.

The model analyzes each viewpoint independently, assessing the chin strap condition (properly worn, unbuckled, loose) as follows,

1) A stricter safety standard is implemented: if either viewpoint detects inappropriate wear, the overall classification is "inappropriate wear."

2) Key findings: Experiments revealed that Detectron2, trained with images from both frontal and side viewpoints, achieved 100% accuracy in determining the helmet wearing state (including unbuckled chin straps and loose chin straps). This demonstrates the effectiveness of the proposed multi-view approach.

3) Significance: This research offers a unique and effective solution for helmet chin strap detection, surpassing existing technologies. The system leverages object detection AI to analyze chin straps from multiple viewpoints, enhancing safety in construction sites.

FUTURE RESEARCH WORKS

Future research may focus on extending this technology to detect other essential safety equipment and attire, further integrating AI into comprehensive safety management systems. Additionally, field trials at various construction sites will help refine the system’s performance and adaptability to real-world conditions.

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